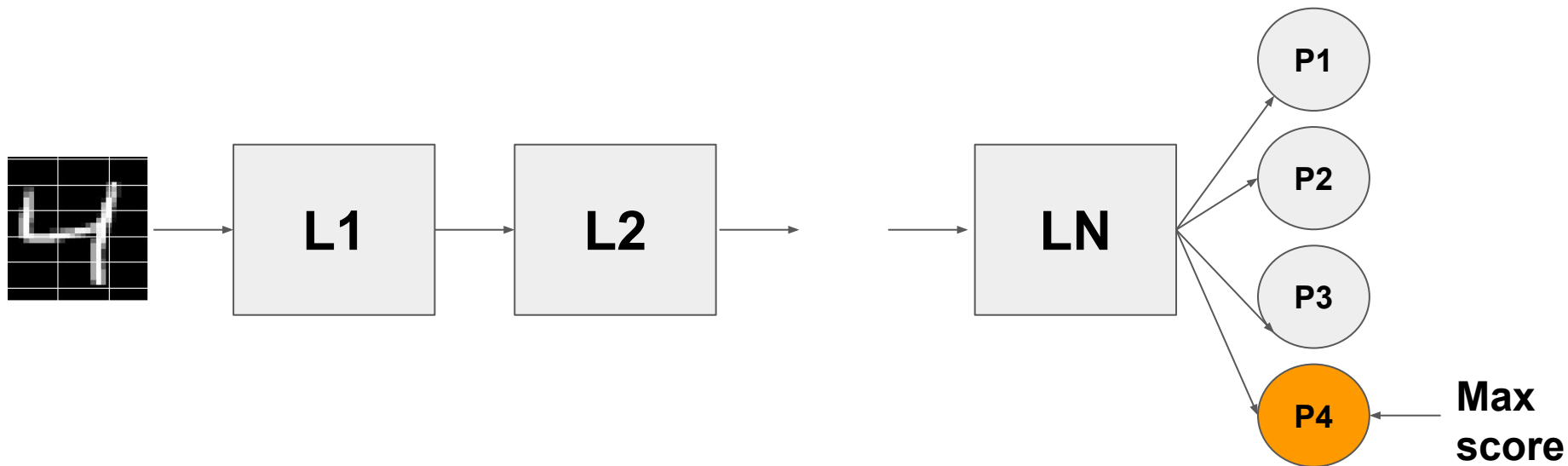


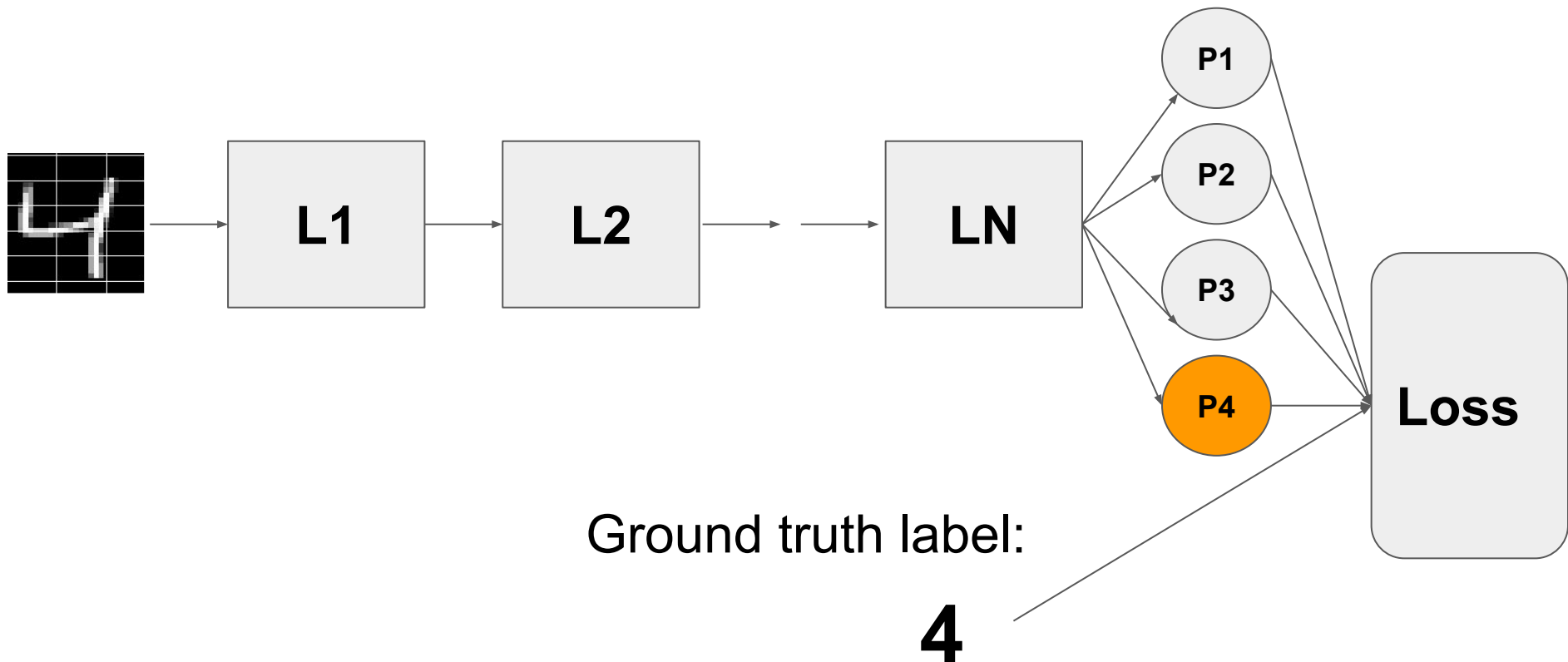
Backpropagation reminder+

29.03.19

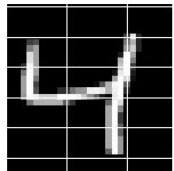
Neural network for multiclass classification



Neural network for multiclass classification: training



Input image



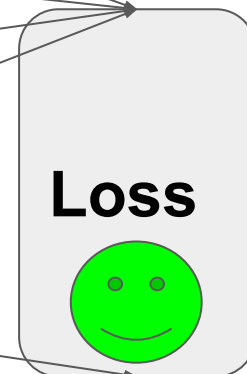
P1

P2

P3

P4

The loss evaluates whether the predictions correspond to the ground truths



Ground truth label:

4

0

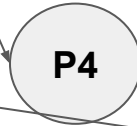
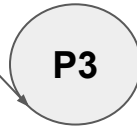
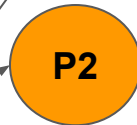
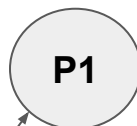
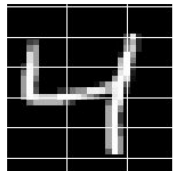
0

0

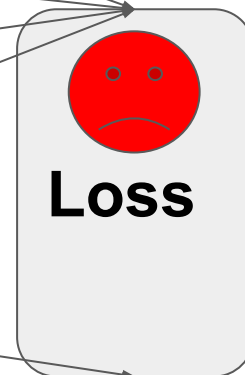
1

Prediction == gt \Rightarrow low loss value, low gradients

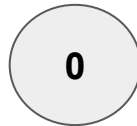
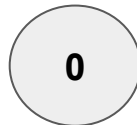
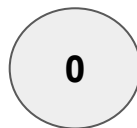
Input image



The loss evaluates whether the predictions correspond to the ground truths



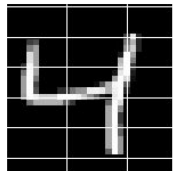
Ground truth label:



4

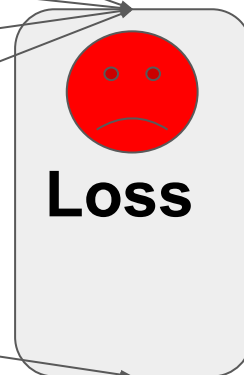
Prediction \neq gt \Rightarrow high loss value,
high gradients \Rightarrow learning

Input image



Punishment

The loss evaluates whether the predictions correspond to the ground truths



Ground truth label:

4

0

0

0

1

Prediction \neq gt \Rightarrow high loss value,
high gradients \Rightarrow learning

Example: log Softmax (used in the code)

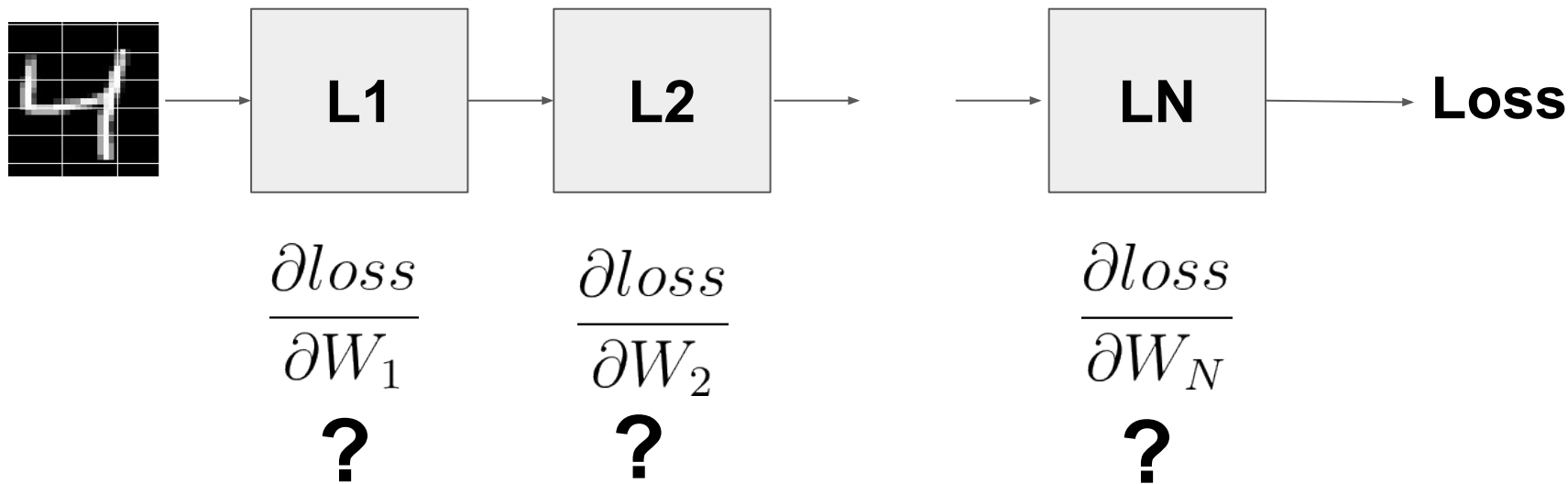
$$loss = -\log \frac{e^{a_{correct}}}{\sum_i e^{a_i}}$$

$$loss = -a_{correct} + \log \sum_i e^{a_i}$$

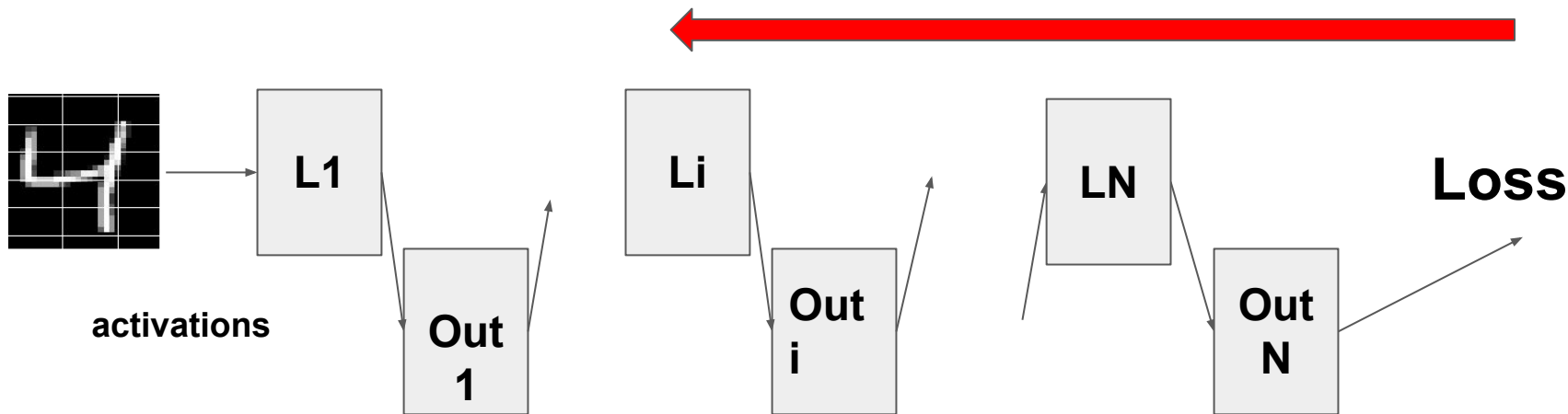
$$\frac{\partial loss}{\partial a}_i = \begin{cases} \frac{e^{a_i}}{\sum_k e^{a_k}} & \text{if } i \neq \text{correct} \\ \frac{e^{a_i}}{\sum_k e^{a_k}} - 1 & \text{if } i = \text{correct} \end{cases}$$

If our prediction is close to ideal => gradients are close to zero

Backpropagation: calculate $\frac{\partial loss}{\partial w}$ for every parameter w



How to calculate $\frac{\partial loss}{\partial w}$




$$loss = loss(Out_N) = loss(Out_N(L_n(Out_{N-1}(L_{N-1}(...Out_i(L_i(Out_{i-1}(...; W_i))...); W_{N-1}))); W_N))$$

$$\frac{\partial loss}{\partial W_i} = \frac{\partial loss}{\partial Out_N} \frac{\partial Out_N}{\partial Out_{N-1}} \cdots \frac{\partial Out_{i+1}}{\partial Out_i} \frac{\partial Out_i}{\partial W_i}$$

Backprop

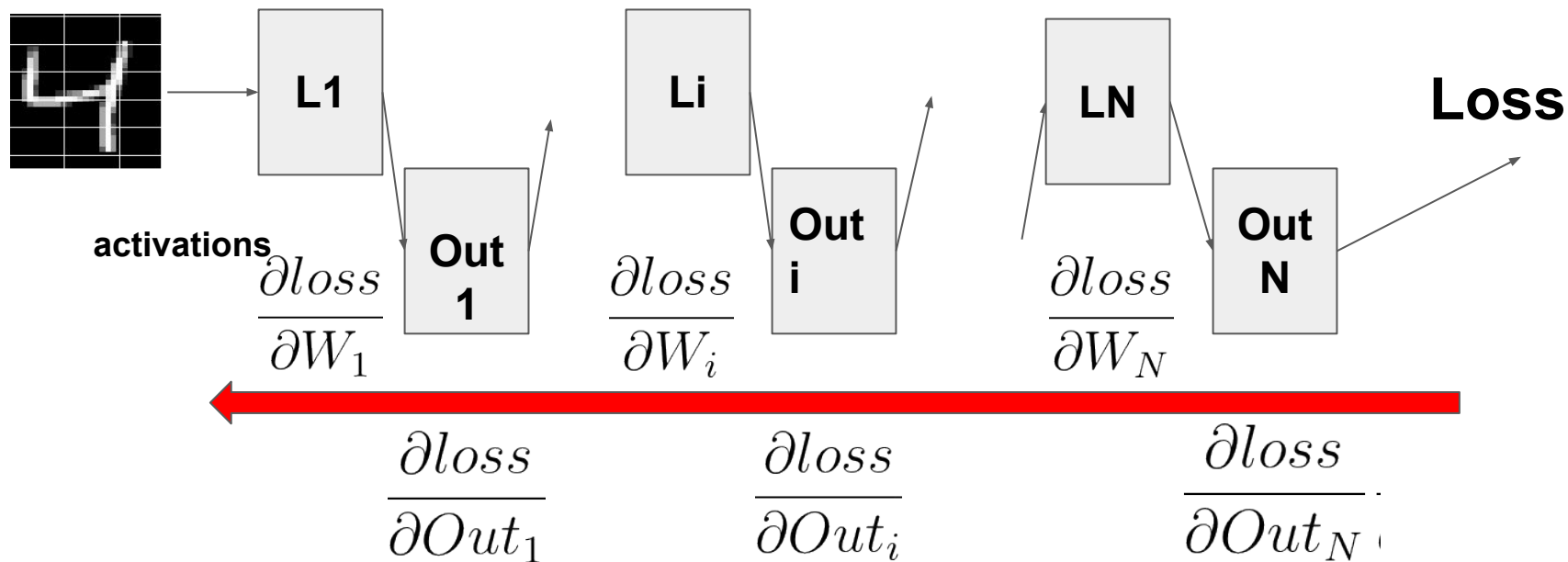
From the last layer to first :

$$\frac{\partial loss}{\partial Out_i} = \frac{\partial loss}{\partial Out_{i+1}} \frac{\partial Out_{i+1}}{\partial Out_i}$$


Known from the
previous iteration

$$\frac{\partial loss}{\partial W_i} = \frac{\partial loss}{\partial Out_i} \frac{\partial Out_i}{\partial W_i}$$

Backprop



Example: dense layer

$$Y = XW + b$$

We have

$$Y = N \times out$$

$$X = N \times in$$

$$W = in \times out$$

$$b = out$$

$$\frac{\partial loss}{\partial Y} = N \times out$$

We need to compute:

$$\frac{\partial loss}{\partial X} = N \times in$$

$$\frac{\partial loss}{\partial W} = in \times out$$

$$\frac{\partial loss}{\partial b} = out$$

Try to guess using sizes,
Consider 1dim case: $y = xw + b$

Dense layer: answers

$$Y = XW + b$$

We have

$$Y - N \times out$$

$$X - N \times in$$

$$W - in \times out$$

$$b - out$$

$$\frac{\partial loss}{\partial Y} - N \times out$$

We need to compute:

$$\frac{\partial loss}{\partial X} = \frac{\partial loss}{\partial Y} W^T$$

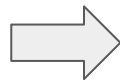
$$\frac{\partial loss}{\partial W} = X^T \frac{\partial loss}{\partial Y}$$

$$\frac{\partial loss}{\partial b} = \sum_i^N \frac{\partial loss}{\partial Y_{ik}}$$

Dense layer: derivation

$$\frac{\partial loss}{\partial X} = \frac{\partial loss}{\partial Y} W^T$$

Y_i only depends on X_i !!!
(examples in the batch are independent)

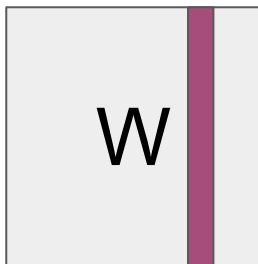
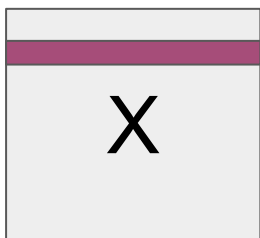
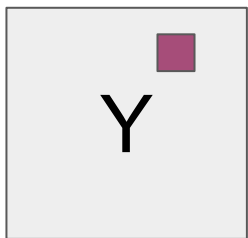


$$\left[\frac{\partial loss}{\partial X} \right]_{ij} = \frac{\partial loss}{\partial X_{ij}} =$$

$$\sum_{k,l}^{N,out} \frac{\partial loss}{\partial Y_{kl}} \frac{\partial Y_{kl}}{\partial X_{ij}} =$$

$$\sum_l^{out} \frac{\partial loss}{\partial Y_{il}} \frac{\partial Y_{il}}{\partial X_{ij}} =$$

$$\sum_l^{out} \frac{\partial loss}{\partial Y_{il}} W_{jl}$$



Beyond classification: image retrieval

- For each query image to find similar images (of the same class) in a gallery set
- Image retrieval vs classification: images of unseen classes are possible
- **The key problem** is to be able to **estimate similarity** value of image pairs so that all the gallery images could be sorted by their similarity to a query image

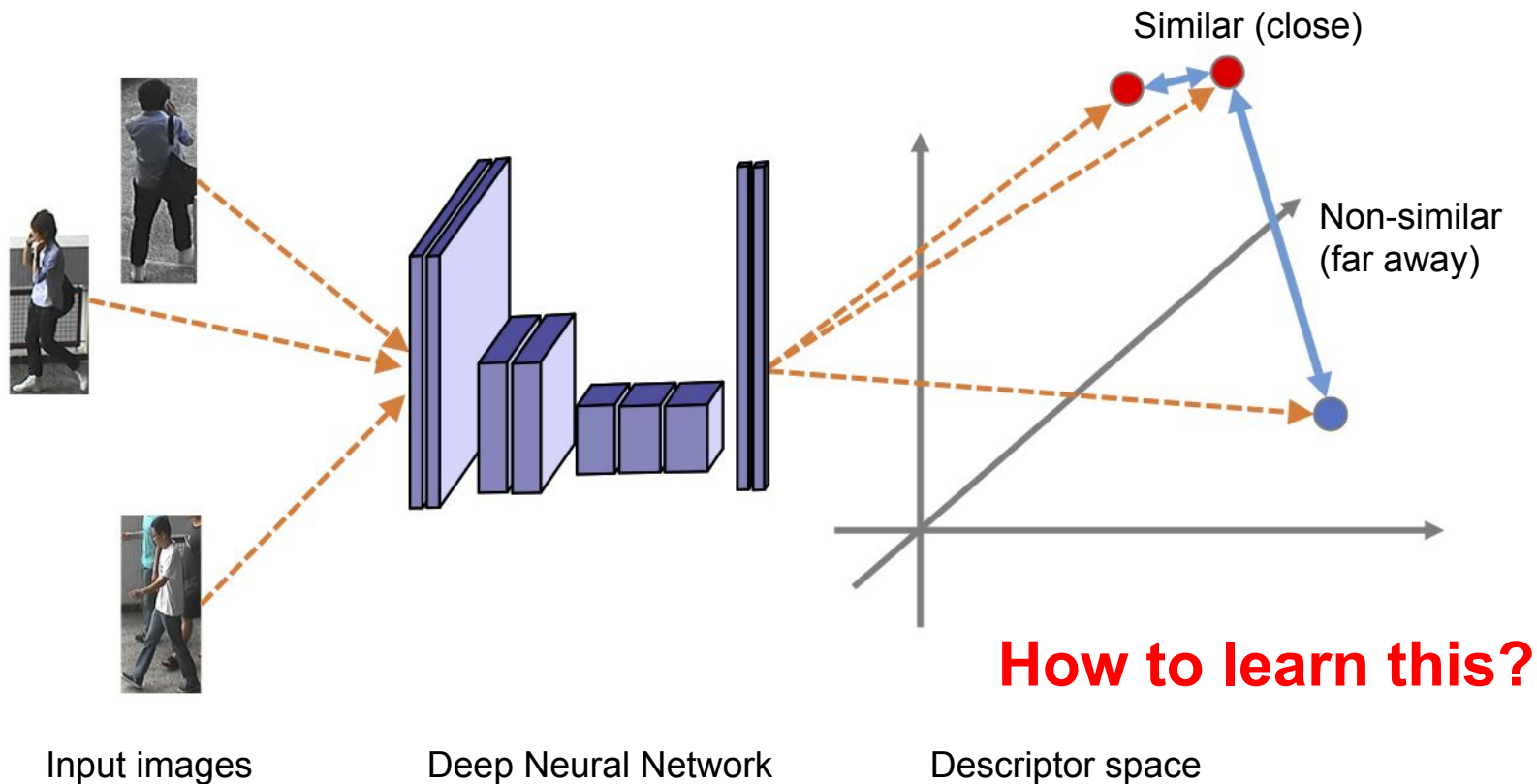
Query image



Matching gallery images



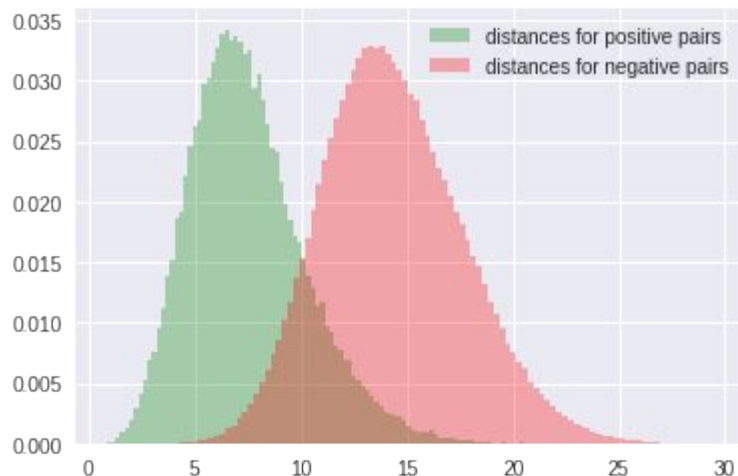
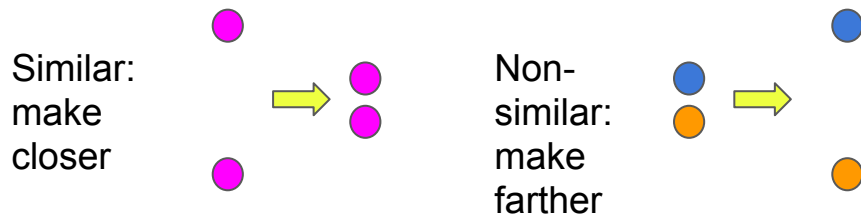
Deep learning for image retrieval



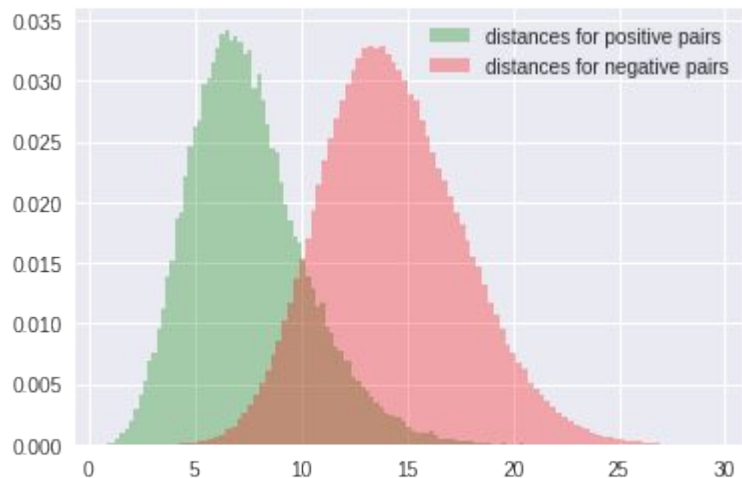
Contrastive loss

$$L_c(x_i, x_j, l) = \begin{cases} \frac{1}{N_{pos}} \|x_i - x_j\|_2^2 & l = 1 \\ \frac{1}{N_{neg}} (\max(0, M - \|x_i - x_j\|_2))^2 & l = 0 \end{cases}$$

Changes in the descriptor space:



Distributions of the distance values



Often, less overlap mean better retrieval
(but of course, there are more direct retrieval metrics)

$$BC(p, q) = \sum (\sqrt{p_i q_i})$$

Bhattacharyya coefficient measures the overlap
(see example in the seminar code)